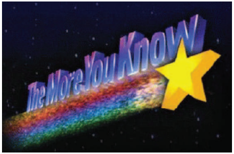
The More you Know - The Information Gain Approach to Path Planning (Part 3 - Branch Entropy)

Liam Paull



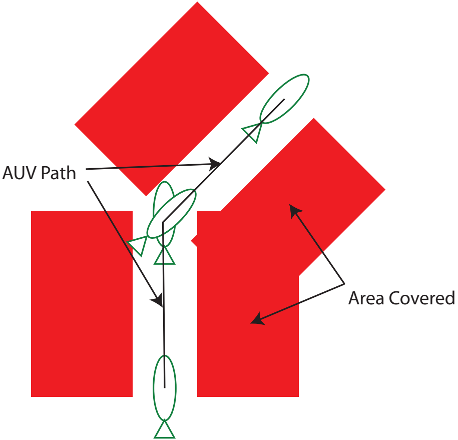
Outline

The Goal of the Mission

$$c_{thresh} \leq c_{avg} = \frac{1}{ij} \sum_{i,j \in W} c_{ij}. \tag{1}$$

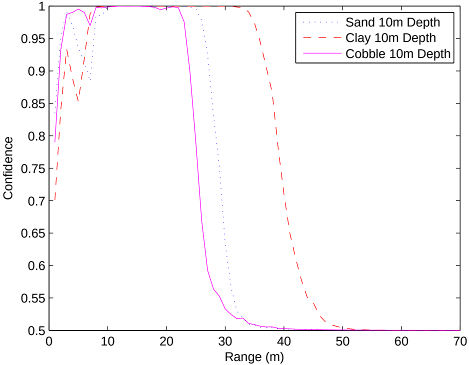
Outline

Sidescan Sonar Geometry



$$p = \bigcup_{i=1}^{n} p_i \qquad (2)$$

Sensor Performance



$$P_{ij} = \begin{cases} c_{ij} & \text{if } T_{ij} = 1 \\ 1 - c_{ij} & \text{if } T_{ij} = 0 \end{cases} \quad (3)$$

Outline

Objective Function

$$R(t) = w_B \cdot B(t) - w_J \cdot J(t) - w_D \cdot D(t) + w_G \cdot G(t). \quad (4)$$

where

B: Information Gain

J: Turning Angle

D: Distance Tranvelled

G: Branch Entropy

Conditional Entropy for a Binary RV

$$H(y|z) = -P\log_2(P) - (1-P)\log_2(1-P), \tag{5}$$

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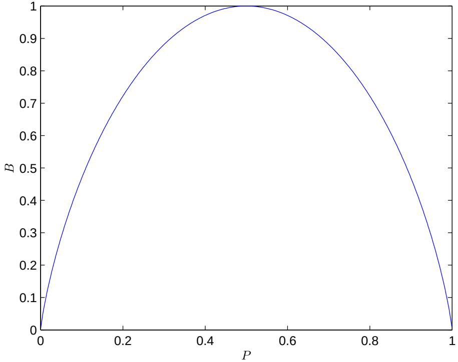
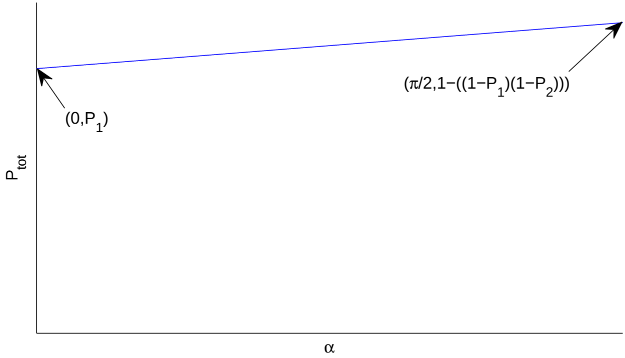


Combining Measurements Based on Angle of Incidence

Linear relationship between dependence and independence

Dependant: $P_{tot} = P_1$

Independant: $P_{tot} = 1 - ((1 - P_1)(1 - P_2))$



Information Gain Approach is Greedy!

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SOLUTION 2: Branch Entropy - A new concept proposed by myself (to be presented at CASE 2010)

Branch Entropy

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Procedure:

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2. Calculate the expected information gain of each node in the graph
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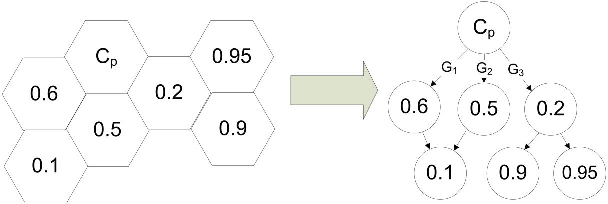
4. Can replace information gain in objective function or be added as a new term

Branch Entropy - Generating the DAG

Here's an example:



Calculating the Branch Entropy

$$G_k = \frac{\sum_{l=1}^{L}(L-l+1)\frac{\sum_{i=1}^{m_{lk}} H_i}{m_{lk}}}{\sum_{l=1}^{L} l}. \quad (6)$$

Where:

G : Branch Entropy

k : Branch

L : Depth of DAG

$m_l k$: Number of nodes at level l of branch k

H_i: Average entropy of node i

Branch Entropy - Advantages

$$G_k = \frac{\sum_{l=1}^{L} (L - l + 1) \frac{\sum_{i=1}^{m_{lk}} H_i}{m_{lk}}}{\sum_{l=1}^{L} l}. \quad (7)$$

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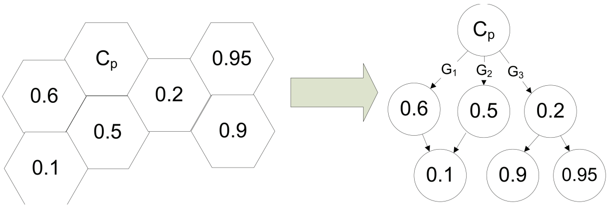
2. Helps the robot finish areas before it leaves
3. Breaks ties in a sensible way, e.g. when robot ends up in a region that is completely covered

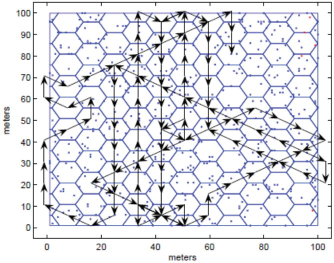
Branch Entropy - Example

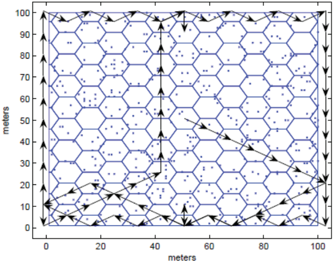


Question: Compute the G_k's

$$G_k = \frac{\sum_{l=1}^{L} (L - l + 1) \frac{\sum_{i=1}^{m_{lk}} H_i}{m_{lk}}}{\sum_{l=1}^{L} l}. \tag{8}$$

Branch Entropy - Some Preliminary Results





Total path taken for information gain approach (left): 1080 meters Total path taken for branch entropy approach (right): 790 meters